Approximation-First Timeseries Query At Scale

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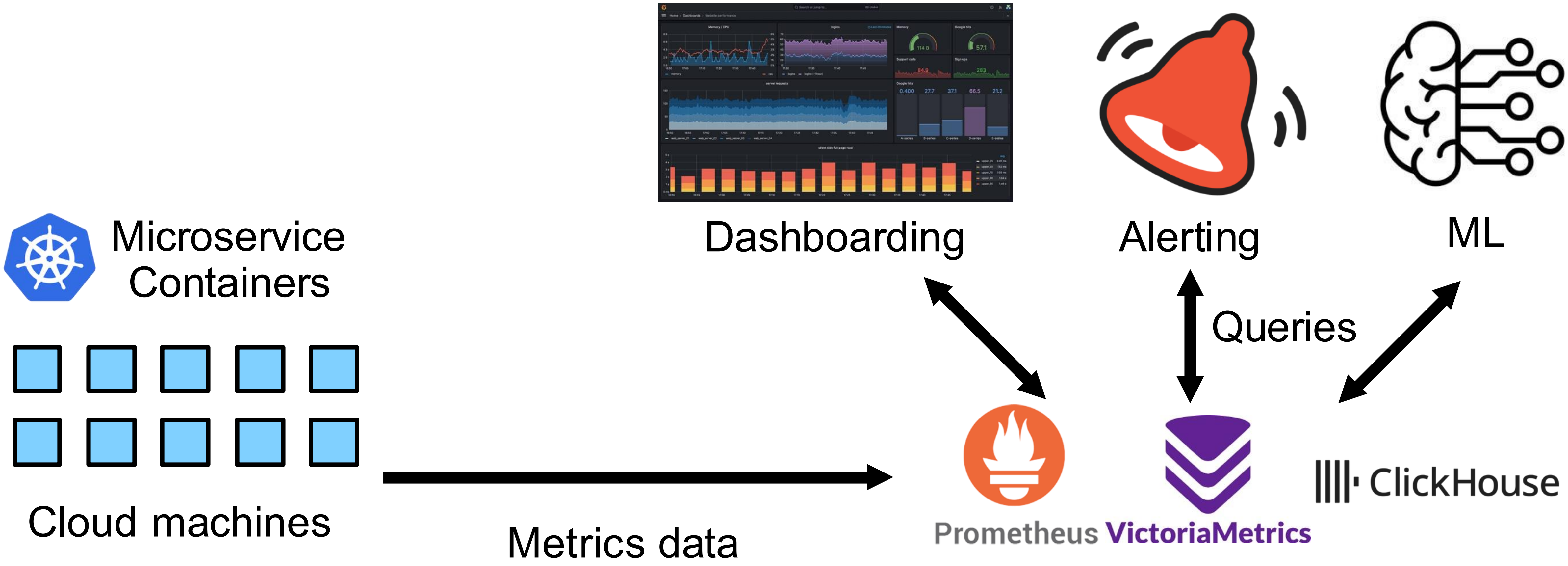
Need for Cloud and Network Observability

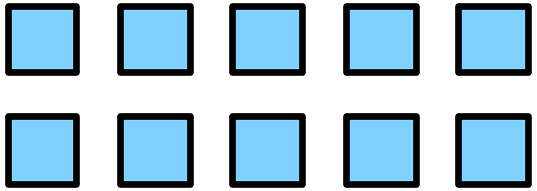


Example: Monitoring Cloud Machines

CPU Usage /Timestamps	5:00:00	5:00:01	5:00:02	5:00:03	…
Host 1	10%	35%	15%	20%	
Host 2	20%	15%	19%	20%	
Host 3	15%	75%	80%	85%	
Host 4	90%	80%	95%	75%	
…					

Queries

Microservice Containers



Cloud machines

Metrics data

Prometheus

Example *Rule* Queries for Cloud Resource Scaling

CPU Usage /Timestamps	5:00:00	…	5:01:00	…	5:02:00	…	5:03:00	…	5:04:00	…	5:05:00	…	5:06:00	…	5:07:00	…
Host 1	10%	…	35%	…	15%	…	20%	…	15%	…	20%	…	50%	…	15%	…
Host 2	20%	…	15%	…	19%	…	20%	…	19%	…	10%	…	40%	…	19%	…
Host 3	15%	…	75%	…	80%	…	85%	…	81%	…	80%	…	83%	…	80%	…
Host 4	90%	…	80%	…	95%	…	75%	…	85%	…	95%	…	80%	…	95%	…
…														…		…

Sliding Window Queries with overlaps between windows

- *Rule* Queries: Periodically (every 1 min) querying 0.95-quantile of CPU usage of last 5 min, for each host.
  - quantile_over_time(0.95, cpu_usage[5m])

Bottlenecks in Window-based Queries

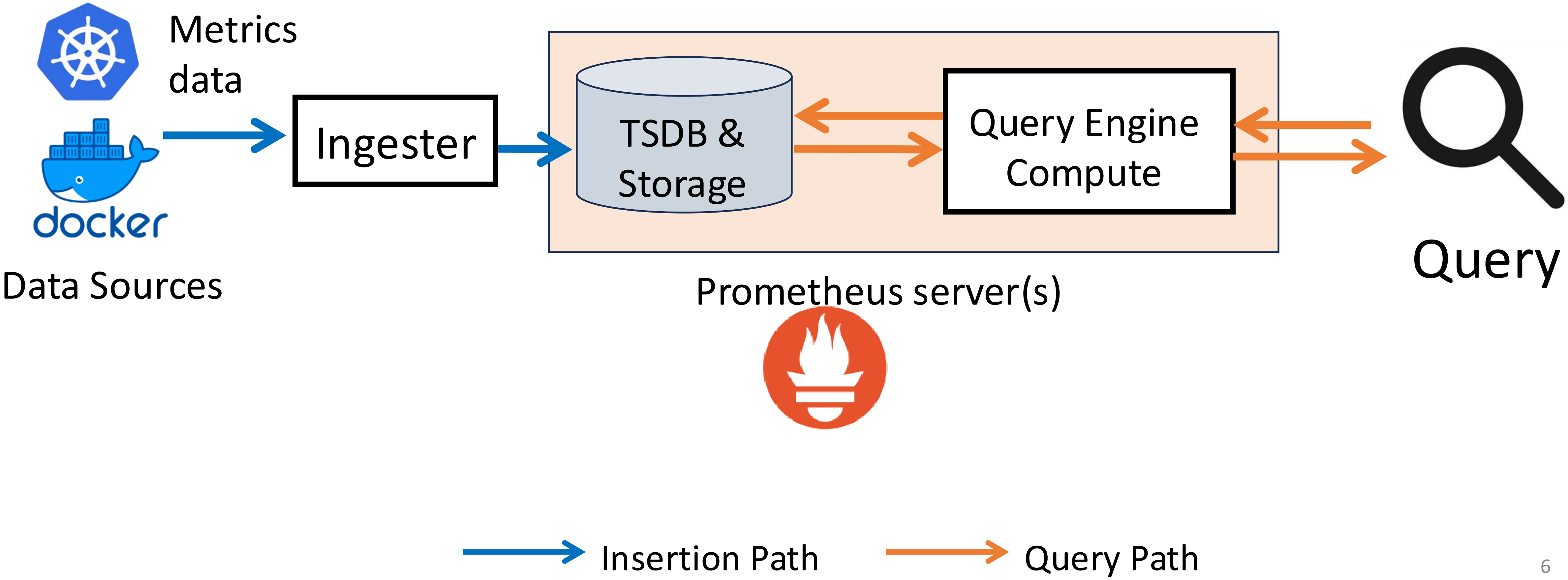
Table 2: CPU hotspots of evaluating a quantile rule query in Prometheus and VictoriaMetrics.

Func/Call Stack	CPU Time		Description
	Prometheus	VictoriaMetrics	
Data Scanning	**41%**	**80.2%**	Fetch data from storage
Query computation	**27.6%**	**11.7%**	Aggregation queries in rule
Go Garbage Collector	24.7%	4.3%	Golang garbage collector
mcall	4.5%	0.8%	Golang runtime scheduling

Major Bottlenecks due to window overlaps:

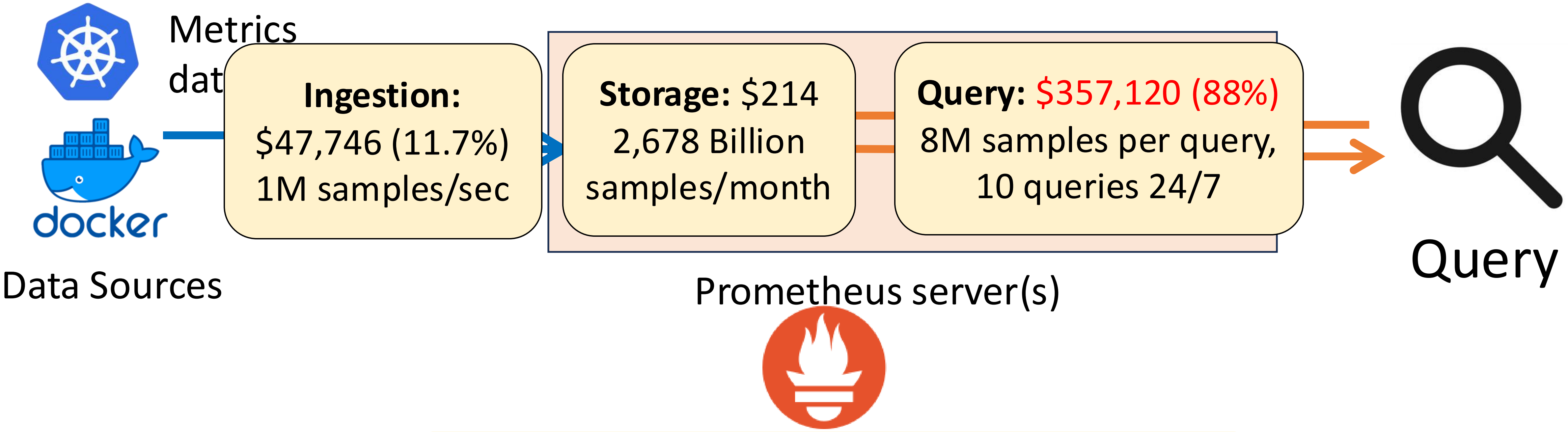
- Repeated data scanning from storage.
- Repeated and heavy query computation.

Prometheus is a Popular Observability Platform



Cloud Monitoring Costs Example

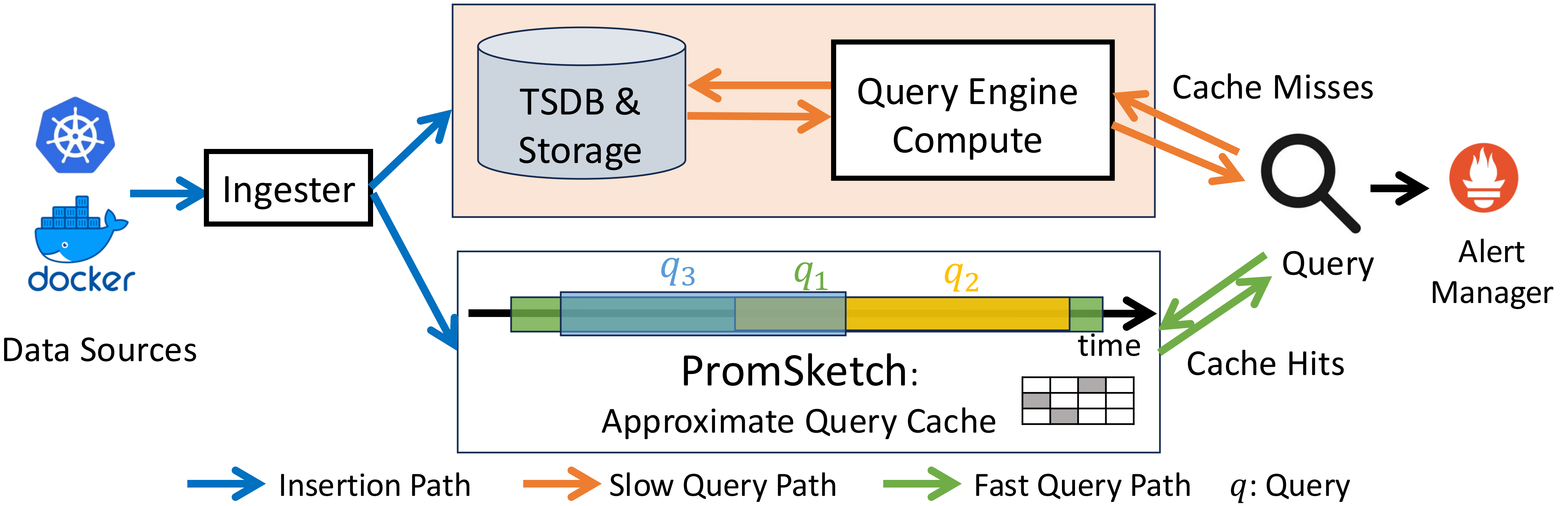
Setup: monitoring 1000-node Kubernetes cluster, each node having 1000 metrics.
AWS Prometheus Pricing: Charge users based on the number of data samples processed.



Query costs are very high in cloud monitoring.

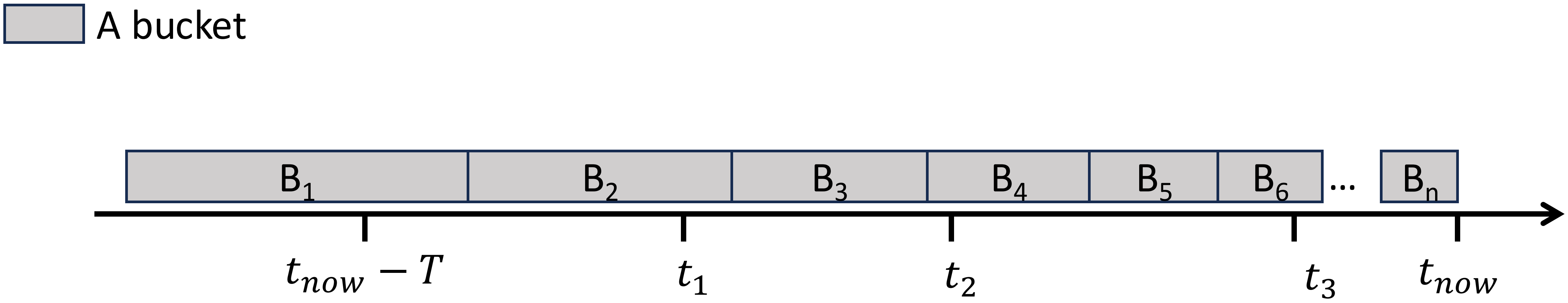
Insertion Path Query Path

PromSketch as an Intermediate Cache



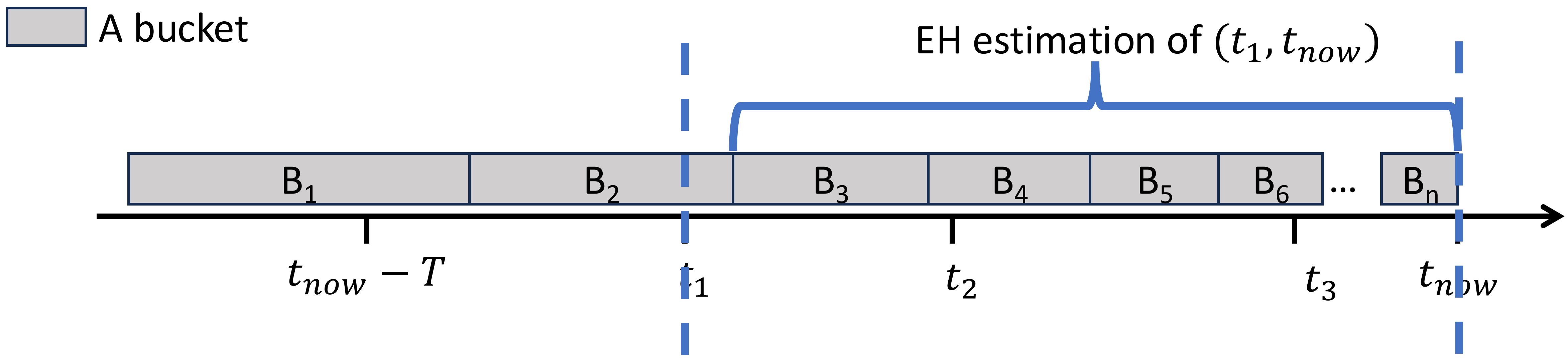
Key Idea: Combining arbitrary sub-window query frameworks and compact sketches as an intermediate query cache, computing overlapping windows once.

Exponential Histogram (EH) Framework



- EH supports querying arbitrary sub-windows cached by most recent T.

Querying Sub-windows by Merging Buckets



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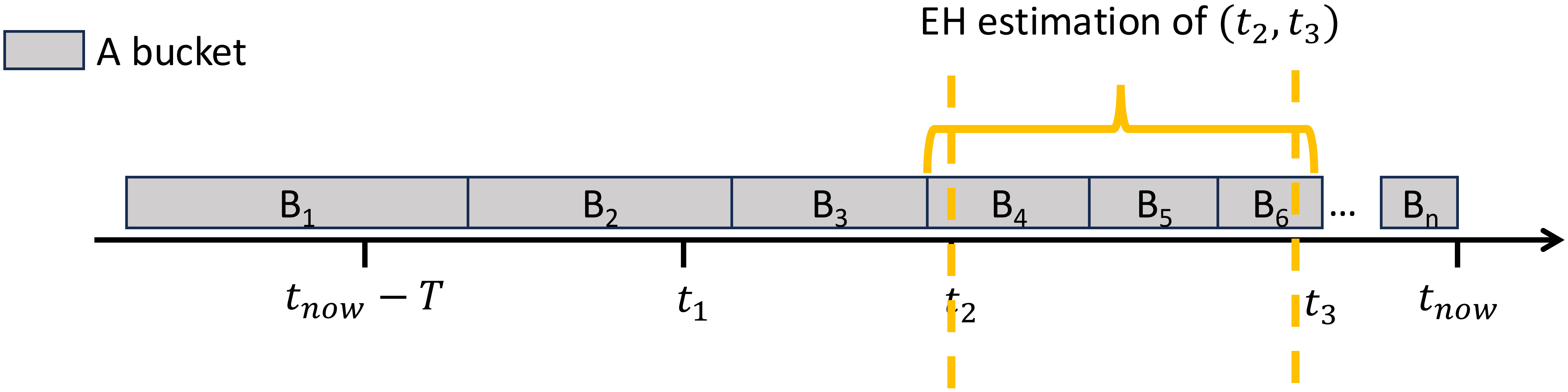
  - Combining buckets closest to the query time range.

Querying Sub-windows by Merging Buckets



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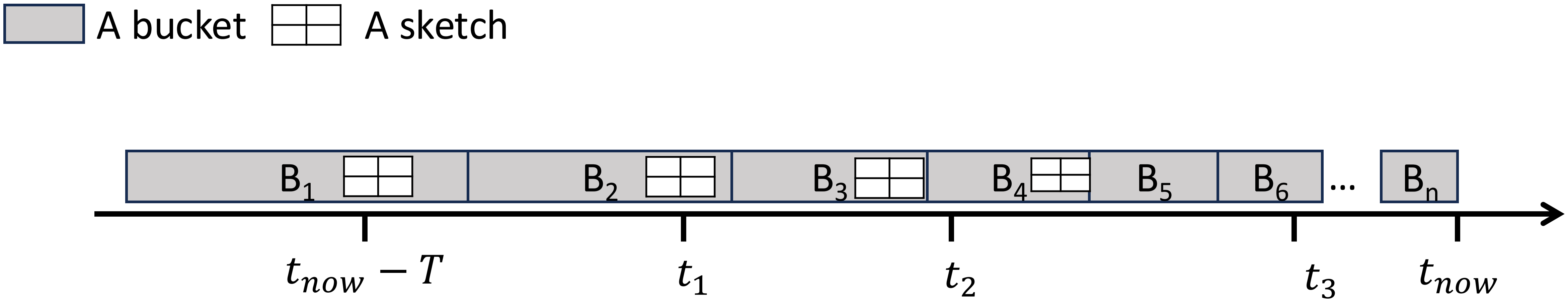
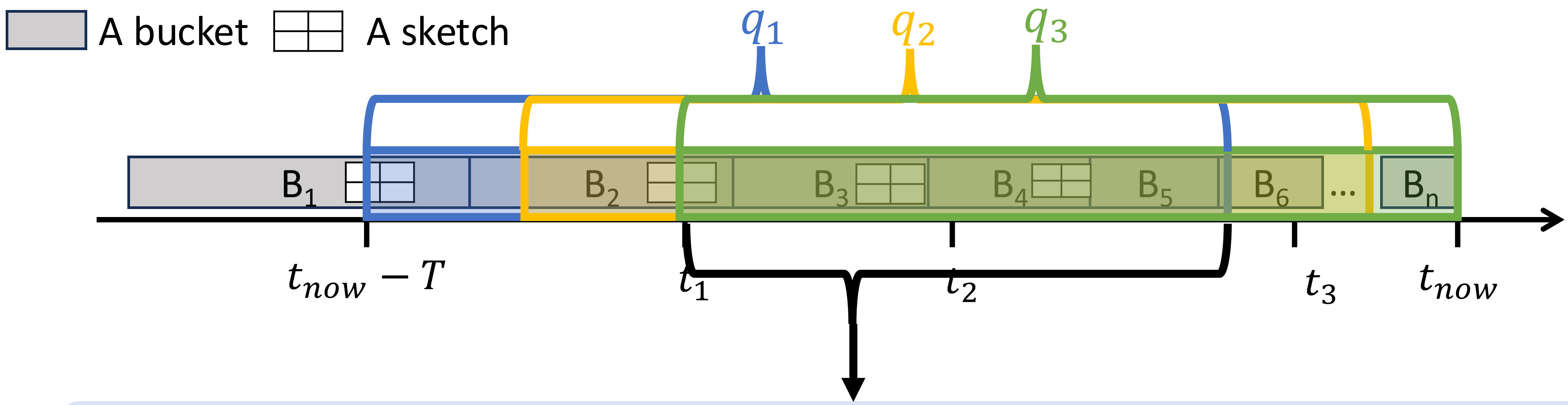
Provable Compact Sketches as Buckets



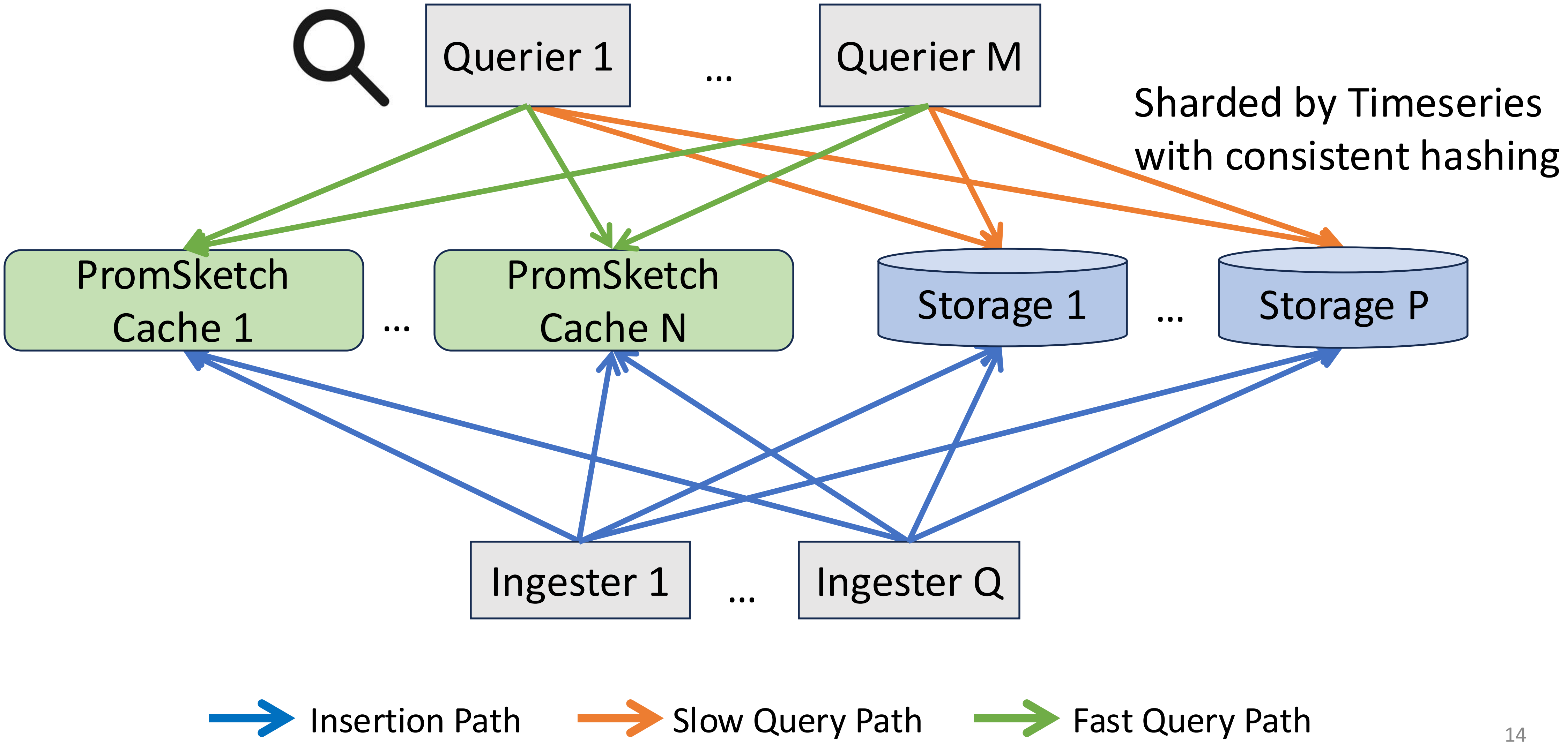
- KLL Sketch for Quantiles, Min, and Max.
- Universal Sketching for a wide range of functions, e.g., cardinality, L2 norm, entropy, top-K finding.

Precomputed Intermediate Cache Eliminates Query Overhead



- Overlapping windows are only computed once and cached in memory.

PromSketch Supports Cluster Version



Evaluation

- Testbed
  - Ubuntu servers with a 32-core CPU, 384GB DDR4 memory, and 1TB Seagate HD
- Baselines
  - Prometheus (single-machine)
  - Single-machine and cluster version VictoriaMetrics
  - Single-machine and distributed PromSketch
- Workloads
  - Google Cluster Dataset 2019 (Google), CAIDA NYU 2018 and CAIDA NYU 2019
  - Dynamic dataset with Zipf, uniform, normal distribution data samples
  - 10 million records

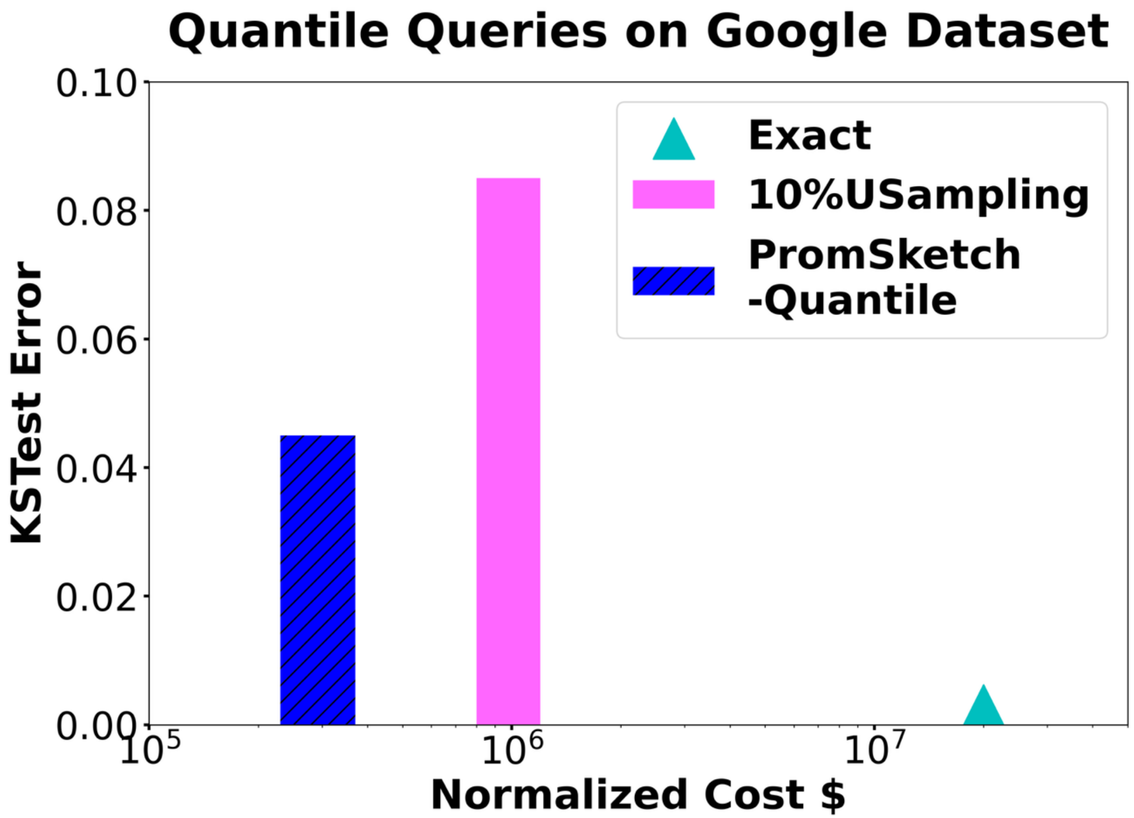
End-to-End Total Concurrent Query Latency

Total concurrent rule query latency on 10K-, 100K-, and 1M-sample windows

Metrics	Prometheus	Prometheus-PromSketch	VictoriaMetrics (VM)	VM-PromSketch
0.9-Quantile	5005 sec	28 sec **(181x ↓)**	96.1 sec	3.2 sec **(30x ↓)**
0.9-Quantile &Max &Average &Distinct	13177 sec	88.6 sec **(154x ↓)**	590 sec	9 sec **(65x ↓)**

- Up to 231x concurrent query latency reduction compared to Prometheus.
- Up to 158x compared to single-machine VictoriaMetrics.

Accuracy-Operational Cost Tradeoffs



- Achieve better cost-accuracy tradeoffs compared to uniform sampling.
- Achieve 5% mean errors with 5x~75x smaller cost compared to exact computation.

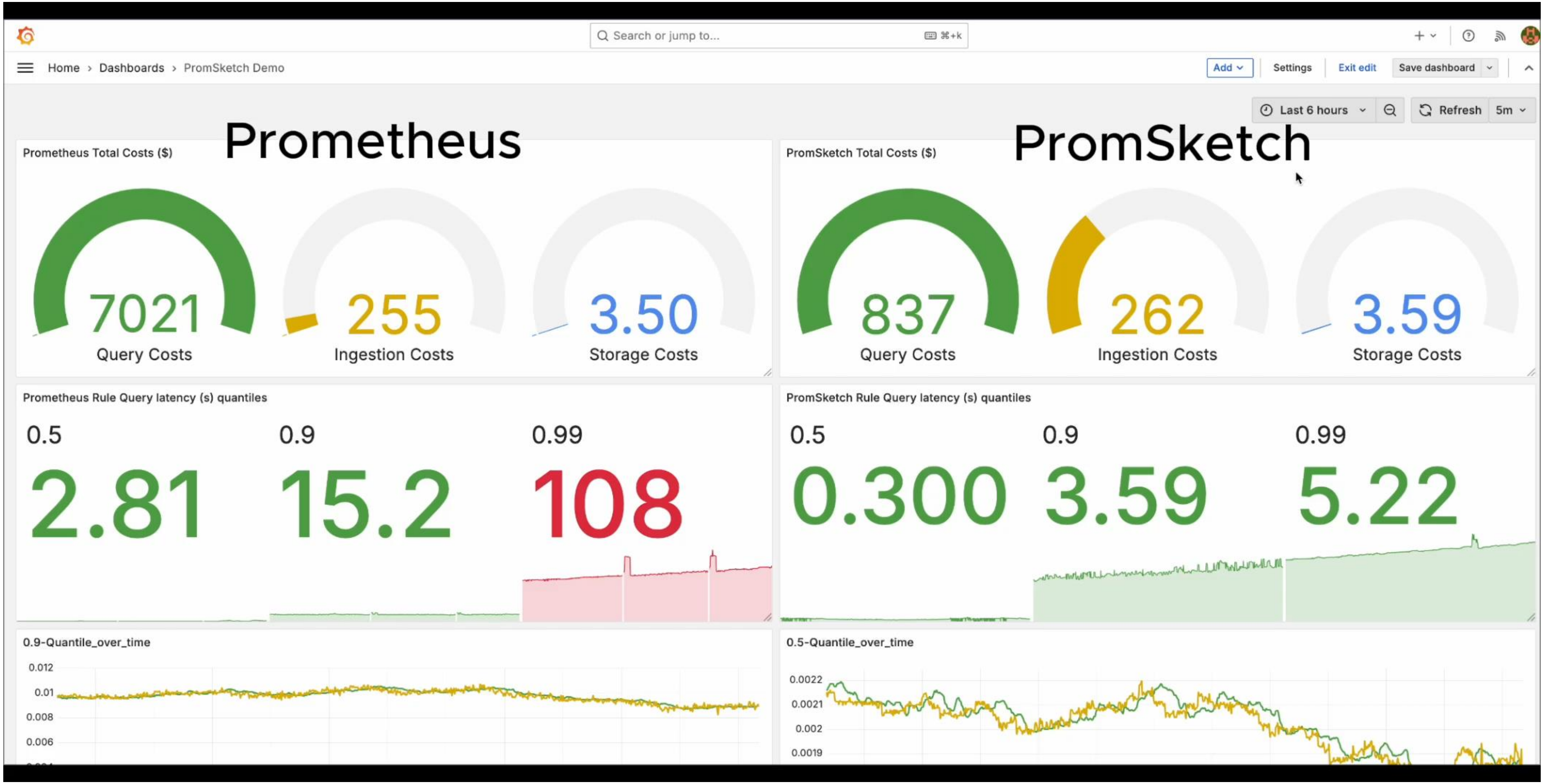
PromSketch Saves Monitoring Costs

Setup: monitoring 1000-node Kubernetes cluster, each node having 1000 metrics.

Resources	Data Volume	AWS Prometheus Costs/Month	Prometheus-PromSketch
Storage	2,678 Billion samples/month	$214	$214
Data Ingestion	1M samples/sec	$47,746	$47,746
Query Processing	8M samples per query, 10 queries running 24/7	**$357,120**	**$267.8 (1,334x ↓)**
Total Costs		$405,080	$48,227.8

- Reducing query costs by up to three orders of magnitude.

It’s Demo Time!



PromSketch Conclusions

- Cloud timeseries monitoring systems, such as Prometheus, incur significant operational costs and high query latency.
- We design PromSketch, an approximation-first query processing framework that leverages sub-window query frameworks and sketch-based precomputation as intermediate caches.
- Integrated with Prometheus & VictoriaMetrics, open-sourced at https://github.com/Froot-NetSys/promsketch.

Thank you!